Challenging the status flow: how artificial intelligence is advancing diagnosis of myelodysplastic neoplasms

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Over the past few years, artificial intelligence (AI) has begun to fulfill its promise of revolutionizing healthcare. In this issue of *Haematologica*, Clichet and colleagues describe how applying AI to flow cytometry parameters improves diagnostic accuracy in patients suspected for myelodysplastic neoplasms (MDS).[1]

Since MDS can be challenging to distinguish from benign cytopenias based on standard diagnostic parameters, multiparametric flow cytometry (MFC) has emerged as an additional diagnostic tool.[2] However, extensive MFC panels with complex analysis strategies are required to achieve adequate diagnostic accuracy. Employing AI may address this issue, given its potential to detect patterns in complex data.[3] While the use of AI in the diagnosis of medical conditions has been a topic of debate, recent advancements demonstrate its benefits in different illnesses such as diabetic retinopathy and breast cancer.[3,4] For both diseases, diagnostic AI tools are currently commercially available and approved for clinical use by regulatory bodies.[3,4]

In the current research, Clichet and colleagues employed an AI model to parameters derived from the MFC data needed for the Ogata score. The Ogata score is the most used MFC score for MDS diagnostics and requires the assessment of only two cell surface proteins: CD34 and CD45.[5] Although the Ogata score is useful and easy to implement, it has limited sensitivity, ranging from 34 to 76%. Clichet and colleagues illustrate that the use of an elastic net AI model resulted in a simple but accurate diagnostic model that only requires four parameters. This model obtained a sensitivity of 91.8% and a specificity of 92.5%, and was validated in an external cohort of 89 patients, illustrating its multi-center potential. One of the explanations for the increase of sensitivity compared with the Ogata score is presumably that this model uses continuous parameters (instead of a fixed cut-off like in the Ogata score) and assigns a weight to each parameter based on its relevance for MDS diagnosis.

A major challenge for AI in healthcare is translating a successful AI model into widespread clinical implementation. Before implementing the model developed by Clichet and colleagues, two initial steps must be taken: extensive multi-center validation and harmonization. Even though most data will be readily available at many locations, such as those collaborating within the European LeukemiaNet working group, harmonization of data acquisition and manual gating strategies of MFC data is crucial. Alternatively, manual gating could be completely replaced by automated analyses, which removes inter-operator variation but requires higher levels of harmonization of data acquisition.[6,7]

Implementing AI-based diagnostics is also challenging in itself, and lack of technical expertise and funding are commonly reported as major obstacles.[8] However, there are examples of innovative solutions that can help facilitate the adoption of AI models in healthcare. One such example is the recently introduced Molecular International Prognostic Scoring System for Myelodysplastic Syndromes (IPSS-M) risk stratification model for MDS, which can be easily employed using a web-based tool that is accessible to all.[9] The availability of a similar tool for the model developed by Clichet and colleagues would make it easier to use and facilitate widespread adoption in clinical settings.

Future development and implementation of AI-based tools for the diagnosis of MDS will largely depend on the availability of high-quality data.[8] The previously mentioned successful studies on AI in diabetic retinopathy and breast cancer cover thousands of patients, spread over multiple centers and continents.[3,4] To fully harness the potential of AI in the diagnosis of MDS, it is crucial that the MDS community joins forces to continue to build comprehensive and diverse databases, such as those managed by the European LeukemiaNet MDS (EUMDS) registry and the MDSRight Consortium. To further improve diagnostic accuracy, these databases should be expanded with data offering high diagnostic potential when applying AI, such as morphological images, mutational

data, and data from novel tools such as label-free cytometry.[10,11]

Overall, we commend Clichet and colleagues for developing an elegant diagnostic model for MDS. By establishing high-quality databases and clear guidelines on how to implement AI-based diagnostic tools effectively, we can further advance the diagnosis of MDS through AI.

Disclosures

No conflicts of interest to disclose.

Contributions

All authors contributed equally to the content of this editorial and approved the final submitted manuscript.

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